Simultaneous Active Learning of Classifiers & Attributes via Relative Feedback

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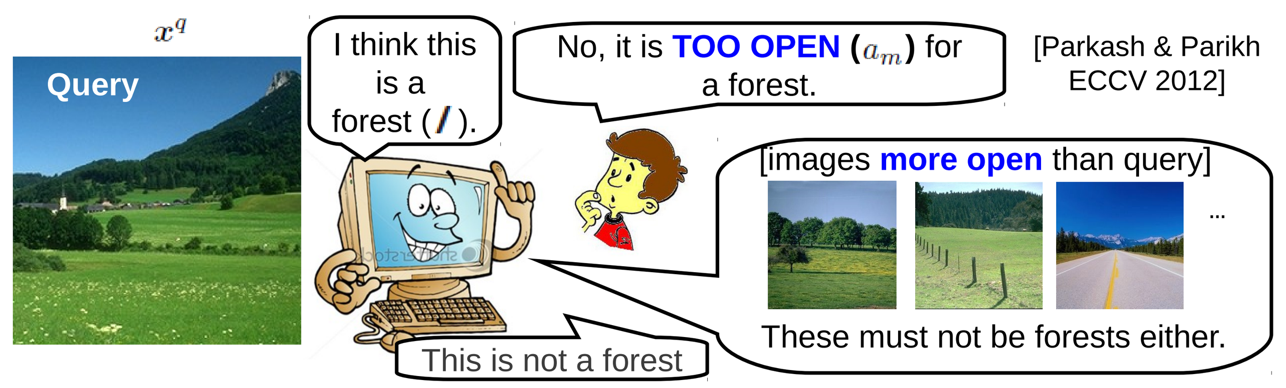
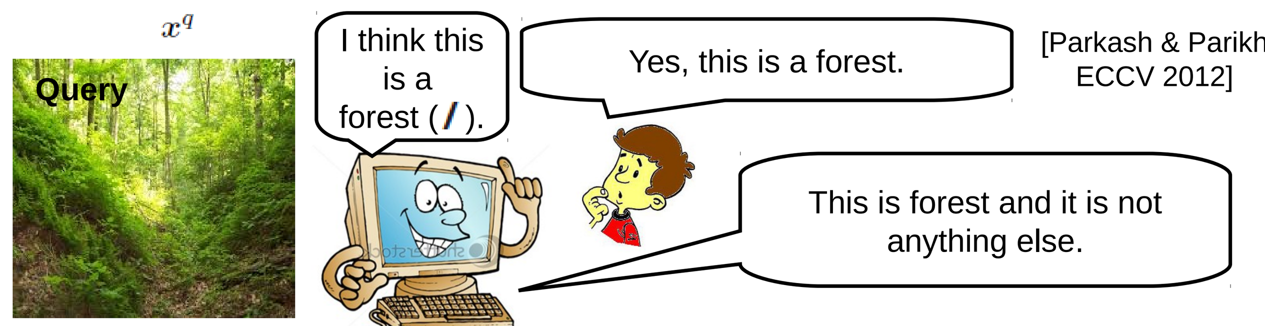
Attributes-based Feedback for Training Classifiers





+ Leads to better discriminative performance than label-based feedback
- Needs pre-trained attribute models
- All negative examples treated to be equally likely
- Query image not selected intelligently

Contributions

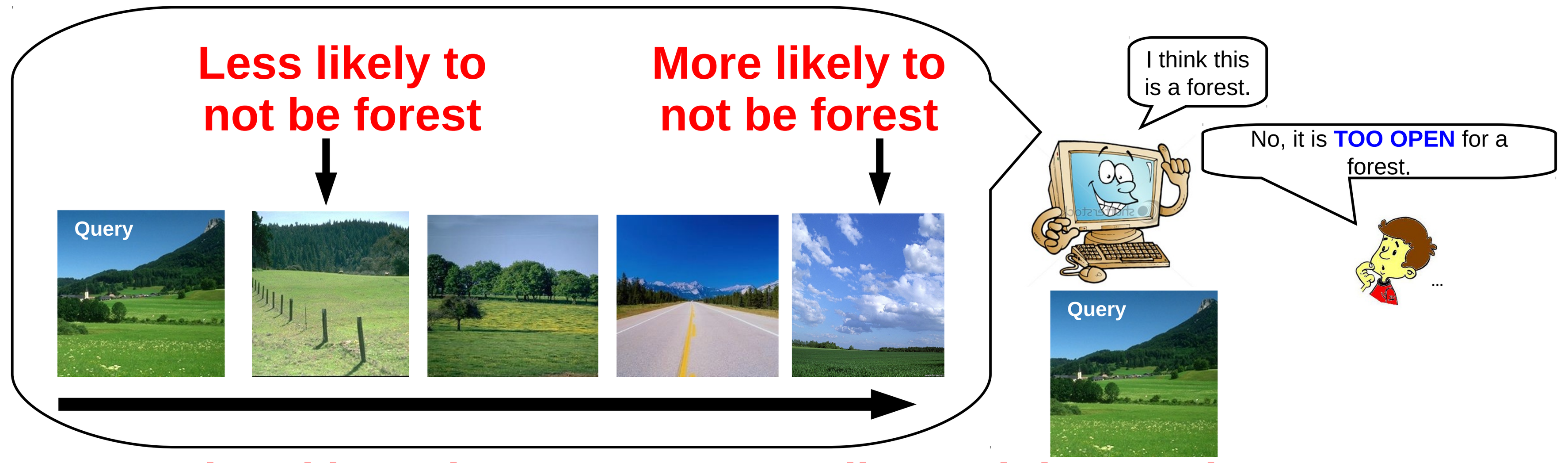
- Learn **attribute & category models simultaneously** on the fly; do not require pre-trained attributes → more flexible & practical
- **Actively select query image** to maximize expected gain from attributes-based feedback → faster learning
- **Intelligently weigh instances** based on feedback → robust learning

- **Large Relative Face Attributes Dataset created!**
  - 60 categories [PubFig, Kumar et al. 2009]
  - 29 attributes
  - **Available online**

'White'
'DarkHair'
'StraightHair'
'Beard'
'GoodLooking'
'young'
'BagsUnderEyes'
'Baldness'
'Chubbiness'
'BushyEyebrows'
'EyesOpen'
'HighCheekbones'
'MasculineLooking/Male'
'MouthOpen'
'Mustache'
'NarrowEyes'
'PointyNose'
'BigNose'
'Nose-to-MouthLines'
'RosyCheeks'
'RoundFace'
'RoundJaw'
'Shiny Skin'
'LongSideburns'
'Smiling'
'VisibleTeeth'
'VisibleForehead'
'WearingLipstick'
'BigLips'

- Large vocabulary of categories; users can only verify
- Realistic in surveillance, bird or leaf recognition

Weighing Negative Examples



Images ordered based on openness attribute, rightmost is most open

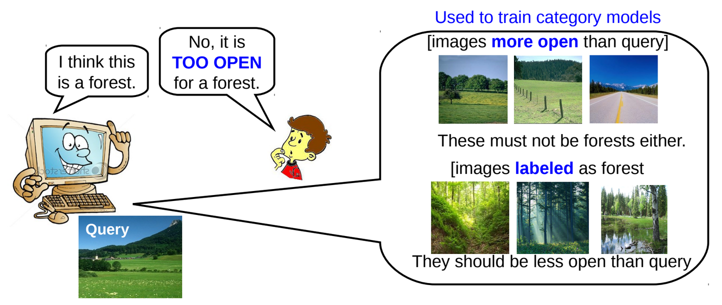
- **$w^l_Q(x)$ captures the likelihood at iteration Q that unlabeled image x is not from class l**
- Computed using attributes-based feedbacks over past iterations

$$w^l_Q(\boldsymbol{x}) = \sum_{q=1}^{Q} n_q(\boldsymbol{x}) \tag{1}$$

- Where $n_q(\boldsymbol{x})$ is 0 if: l was not predicted label for $\boldsymbol{x}^q$ **OR** l was correctly predicted **OR** $\boldsymbol{x}$ does not have more a_{m^q} (attribute feedback at iteration q) than $\boldsymbol{x}^q$ i.e. attribute strength $r_{m^q}(\boldsymbol{x}) < r_{m^q}(\boldsymbol{x}^q)$
- Otherwise, $n_q(\boldsymbol{x})$ is number of images between $\boldsymbol{x}^q$ and $\boldsymbol{x}$, when sorted by attribute a_{m^q}

Simultaneous Attribute and Category Learning

- **Do not need pre-trained attributes!**
- User can introduce any attribute at any time; highly flexible
- If user says: "$\boldsymbol{x}^q$ is too a_m to be l":
  - learner fetches images labeled as l
  - appends O_m with constraints $O_m = O_m \cup \{(\boldsymbol{x}^q, \boldsymbol{x}_j)\}$
  - where, $\boldsymbol{x}_j$ s have been labeled as l and O_m are ordering constraints used to train a_m



Used to train attribute models

Active Selection of Images

- Select image that reduces expected system entropy the most
- **Novel active learning algorithm in attribute based feedback setup**

$$\text{Present Entropy of system: } H = -\sum_{i=1}^{N}\sum_{k=1}^{K} p_k(\boldsymbol{x}_i)\log(p_k(\boldsymbol{x}_i)) \tag{2}$$

- $p_k(\boldsymbol{x}_i)$ is probability of image $\boldsymbol{x}_i$ belonging to class k (according to classifier h_k) and N is number of images in unlabeled set

Select the image which reduces expected entropy of the system

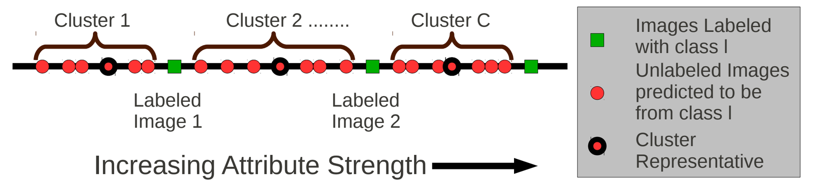
- Expected change in entropy of system:

$$\Delta H(i) = H - \left(p^0 H^0 + p^1\left(\sum_{m=1}^{M} p_m^{1+} H_m^{1+} + \sum_{m=1}^{M} p_m^{1-} H_m^{1-}\right)\right) \tag{3}$$

- **p^0 is the probability that the user accepts label for x_i**; H^0 is resultant entropy of system
- **$p^1 = 1 - p^0$ is the probability that the user rejects label and provides an attributes-based feedback**; H^1 is resultant entropy
- There are $2M$ possible feedback statements (M attributes, "too" or "not enough")
- Chances of the supervisor picking any of M attributes with "too" response is p_m^{1+} and "not enough" response is p_m^{1-}.
- Resultant entropy of the system is H_m^{1+} and H_m^{1-} respectively.

Efficient Active Selection:

- **Brute force method to find best image has high computational cost**
- Requires learning $2NM$ ranking functions at each iteration
- We propose a fast approximation by clustering
- Train ranking function only for every cluster center instead of every image
- **Need to train only 5 – 7% ranking functions**



Collecting Relative Attribute Data from Mturk

- **Exhaustive data collection to run experiments automatically while still using feedback from real users**
- Show example images from a pair of categories to 10 workers on Mturk and **ask which category has a stronger presence of attribute**

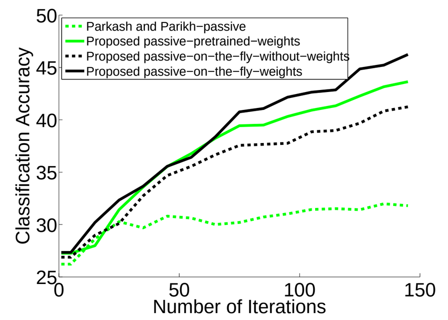
- **Two interfaces used for experiments:**
  - Mturk workers provide free form attribute feedback
  - Mturk workers choose an attribute from a list that corresponds to the most obvious difference between the two categories

Experimental Results

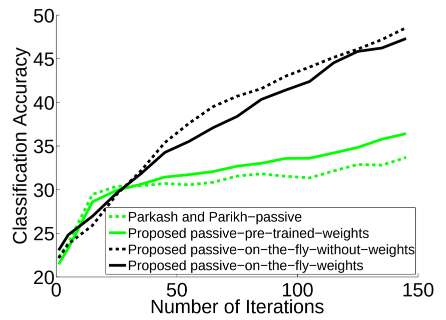
Name of Method	Attribute Feedback Used	Weighting Scheme Used	Attributes Learned	Query Image Selection
Baseline passive	no	N/A	N/A	random
Baseline active	no	N/A	N/A	max-entropy
Parkash & Parikh -active	yes	no	pre-trained	max-entropy
Parkash & Parikh -passive	yes	no	pre-trained	random
Proposed passive-pre-trained-weights	yes	yes	pre-trained	random
Proposed passive-on-the-fly-without-weights	yes	no	on-the-fly	random
Proposed passive-on-the-fly-weights	yes	yes	on-the-fly	random
Proposed active-maxent-on-the-fly-weights	yes	yes	on-the-fly	max-entropy
Proposed	yes	yes	on-the-fly	proposed

Table: Summary of the algorithms that we compare

- Run experiments in two different domains **faces and shoes**
- **Weighing negative samples improves performance**; especially with pre-trained attributes
- **Learning attributes on the fly** lets us add more correct negative examples to the classifier
- **No pre-training cost but better classification with attributes on the fly!**

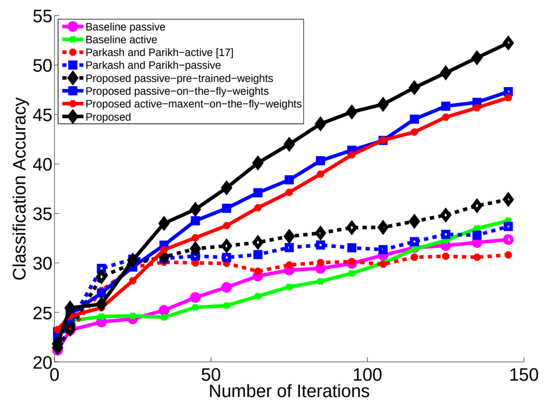


(a) Shoes-750-10

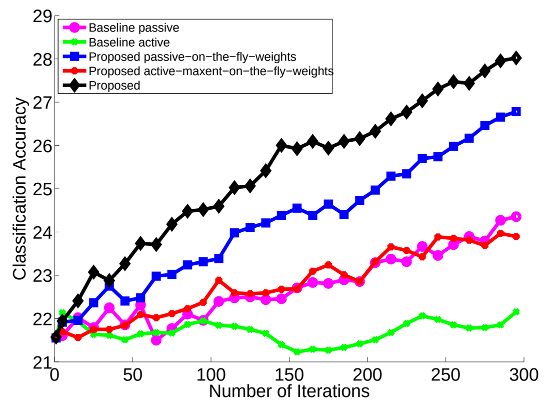


(b) Pubfig-772-8

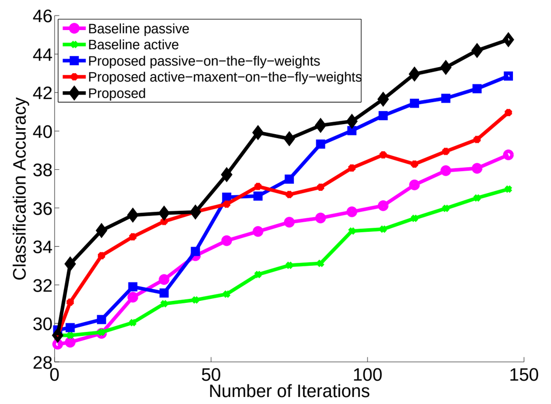
Figure: Impact of our proposed weighting scheme and of learning attribute models on the fly on performance



(a) Pubfig-772-8



(b) Pubfig-900-60



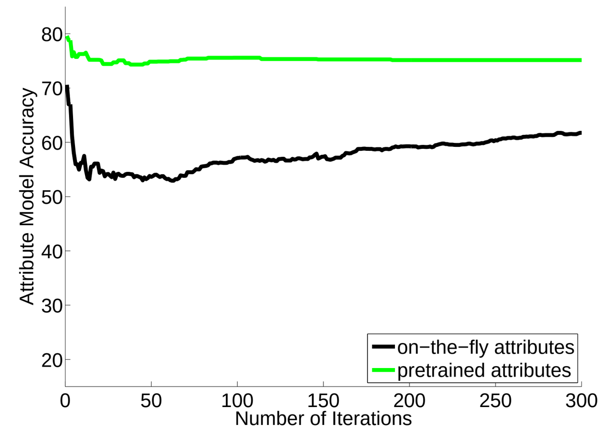
(c) Shoes-750-10

Figure: Comparing our proposed approach to various baselines (Table above)

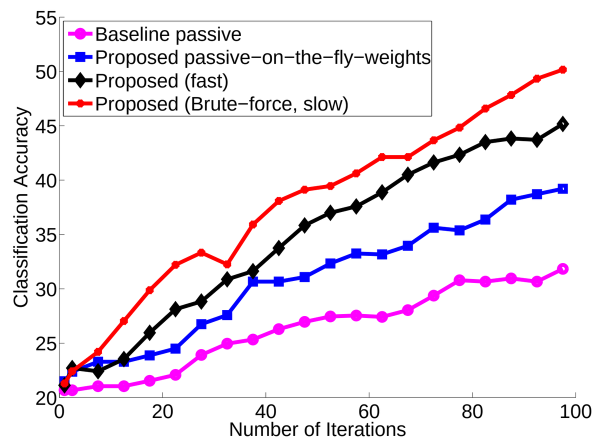
- **Our active method outperforms the passive and traditional maximum entropy image selection methods**

Additional Experiments

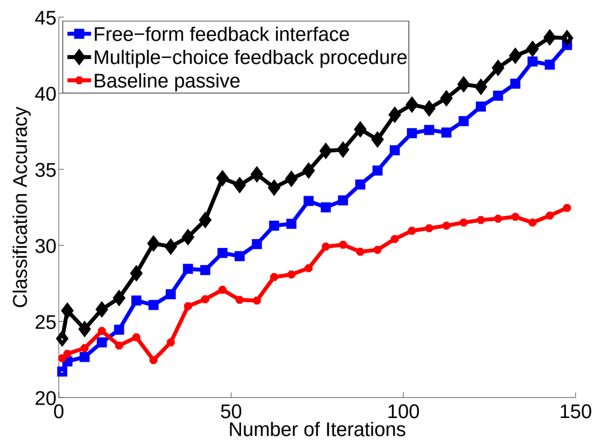
- Fast active approach is not a lot worse than brute force (tested on a smaller dataset)
- Attribute models learned on the fly are worse as attribute predictors in general
- We **compare our two interfaces** for data collection
  - **Ideal: a system where people can provide free form attribute feedback**
  - **However that involves natural language processing: future work**



(a) Quality of attribute predictors



(b) Comparison to brute force



(c) Free-form attributes-feedback

Figure: (a) Attribute models learnt on the fly are worse attribute models per say, but are better suited for providing classifier-feedback than pre-trained attribute models. (b) Our clustering-based fast active learning approach does not perform significantly worse than the brute-force version of our approach which would be prohibitively slow. (c) A comparison between two interfaces for collecting attributes-based feedback

Conclusion

- **We extend the relative attributes-based feedback setup for learning classifiers: more accurate, robust and practical**
- Gain in classification accuracy by **significant margin**
- **Collected and made available Relative Face Attributes Dataset** for 60 classes

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